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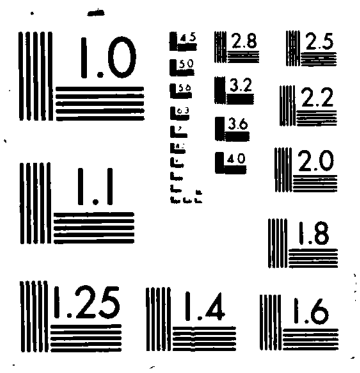
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AN ARTICIFIAL INTELLIGENCE TECHNIQUE FOR
AUTOMATING SEISMIC STRATIGRAPHIC INTERPRETATION

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Submitted to *Geophysics*, November 25, 1986

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

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Abstract

Studying the character of reflected seismic wavelets may reveal facts about the stratigraphy of the reflector. Computers can aid humans in this task by revealing structural similarities between various wavelets. The relational tree is a good way to represent a waveform's global structure. By representiing a waveform as a relational tree, processing it symbolically, and clustering the processed trees, a seismic waveform recognition system can be constructed. The symbolic processing is based on a tree transformation. An objective function, which measures the effectiveness of such a transformation, utilizes the ratio of between-cluster to within-cluster scatter. The action of a tree transformation applied to tree spaces is the same as linear discriminants applied to feature spaces. When tested on simulated seismic data, the relational tree waveform recognition system performs well at high signal-to-noise ratios.

[1] This work supported by NASA grant NGT 44-006-806, AND ONR contract N00014-85-K-0152

ABSTRACT

Studying the character of reflected seismic wavelets may reveal facts about the stratigraphy of the reflector. Computers can aid humans in this task by revealing structural similarities between various wavelets. The relational tree is a good way to represent a waveform's global structure. By representing a waveform as a relaional tree, processing it symbolically, and clustering the processed trees, a seismic waveform recognition can be constructed. The symbolic processing is based on a tree transformation. An objective function, which measures the effectiveness of such a transformation utilizes the ratio of between-cluster to within-cluster scatter. The action of a tree transformation applied to tree spaces is the same as linear discriminants applied to feature spaces. When tested on simulated seismic data, the relational tree waveform recognition system performs well at high signal-to-noise ratios.

INTRODUCTION

Currently available seimic processing techniques, when applied to properly acquired data can produce stacked seismic sections which contain a large amount of stratigraphic information. If a high-bandwidth source wavelet is used, analyzing the shape of a reflected event may reveal details about the reflector lithology. In this paper, we show how computers may be used to automate the analysis of the reflection character. The developments here are based on the premis that there is significance in the lateral variation of the reflection character in a seismogram. For this reason we postulate that computers can aid humans in discovering stratigraphically significant anomalies. We wish to extract information from individual waveforms and classify reflections based on waveform morphology. The technique discussed here is to be applied to sets of isolated reflections. This is not a global processing technique to be applied to entire traces over the whole data set as are the operations commonly associated with seismic data processing. The system consists of local actions to be performed on waveforms which have been conventionally processed and then extracted from a larger data set. Our technique involves symbolic representations and processing routines of the type associated with artificial

intelligence.

There are data structures which represent signals in such a way that specific waveform properties are emphasized. These properties may have to do with a wavelet's overall stuructural character. Such data structures are constrained to a finite set by some grammar which describes the waveforms we expect to encounter. Given these syntactic constraints, machine processing may be designed which intelligently exploits what is already known. This represents an algorithmic approach to signal processing and classification. Waveform processing techniques to date have relied heavily on signal representations consisting of regularly spaced, sequential, digital samples. The algorithms and hardware developed so far have exploited the characteristics of this type of representation using matrix manipulation and numerical computation. We intend to describe an alternate stucture for signal representation, and introduce processing techniques that exploit the a priori constraints on this representation.

We examine some of the techniques developed to date and introduce a waveform recognition system that utilizes tree signal representations, symbolic processing, and non-parametric clustering techniques. The system will then be applied to noisy synthetic seismic data so that we may observe the resulting classification error.

The waveforms in question are represented in such a way that their global structure is emphasized. This representation, known as the **relational tree**, describes the relative placement of peaks and valleys within the waveform. The relational tree is then manipulated by a **tree transformation** so that critical information is preserved, and superfluous information is stripped away. A **tree cluster objective function** is introduced to measure the success of the tree transform. Traditional cluster analysis techniques are then adapted to classifying individual trees.

WAVELET CHARACTER INTERPRETATION

Analysis based on visual inspection by experienced humans remains the most reliable seismic interpretation technique. For this purpose, The interpreter must assimilate the large amount of information available in modern, high-resolution siesmic data. Much of this information lies not only

in the time of arrival of a reflection event. but also in the **character of the reflected wavelet,** a much subtler indication of geology. Under ideal conditions, the presence of reflectors less than 1/8 wavelength thick can cause variations in reflection character (Sherrif, 1977). It is not clear, however, that the human eye is able to detect these variations. A complex reflection may be made up of the superposition of many wavlets with varying amplitude, phase, and offset (Dobrin, 1977). Small fluctuations in wavelet character caused by changing lithology are usually ignored in favor of a macroscopic view of the subsurface. Here are a few examples where the reflection character was utilized to formulate a complete subsurface interpretation.

Numerous case studies indicate that small variations in reflector stratigraphy lead to subtle lateral variation in reflection character. Hydorcarbon indicators such as bright spots and oil-gas interfaces have long been known by seismic interpreters, but small changes in waveform character may indicate more about lithology. (Waters and Rice, 1975) showed by a series of synthetic seismograms that lateral variations in waveform result from facies changes in the Pennsylvanian Morrow Formation. These effects were then compared to observed reflection data. In a study over a producing gas field, Focht and Baker, (1985) related the seismic effects of varying porosity and gas accumulation in the Colony Sandstone Formation of southern Alberta. They illustrated how constructive interference between various reflectors within the Colony contributes to the total reflection signature. As the stratigraphy of the Colony varies horizontally, so does the character of the reflected wavelet. By relating this character to synthetic seismograms taken from producing wells, Focht and Baker were able to quantify these effects and predict the lithology at undrilled locations. They demonstrated that the makeup of the Colony reflection at a certain point is determined by the amplitude, polarity, and offset of the various individual interfaces within the Colony sand. Chapman and Schafers (1983) give evidence that the presence of a shallow sand channel in the Illinois Basin produces a marked reflection character change.

Though experienced humans are currently the best interpreters of seismic waveforms. The descisions they make can not always be quantified

and traced to some underlying physical priciple. Often, they are based more on intuition and past observations rather than on in-depth understanding of a physical model. The algorithms associated with artificial intelligence have been developed to imitate humans, who excell at this type of heuristic reasoning. Within narrow fields of expertise, computers can sometimes perform as human experts do. Presumably, humans derive certain cues from waveform structure. If a machine can recognize waveforms by using these cues, it could also augment those cues with some of its own, processing individual reflections to extract information that cannot be observed through visual inspection.

RELATED WORK

Previous attempts have been made to apply pattern recognition techniques to seismic waveforms. As early as 1969, Mathieu and Rice (1969) extracted features from seismic wavelets and used multivariate analysis to detect stratigraphic anomalies. Later, Waters and Rice (1975) applied statistical cluster anaysis in the search for statigraphic traps. Recently, Sinvahl, et. al. (1984) have quantified some predictors of lithology which are deriveable from seismic reflection data. Variables such as autocorellation values, and reflected frequencies taken at various points were used as features. Discriminant analysis was then applied to optimize clustering, and reduce dimensionality. An attempt was made to model lithologic sequences as Markov processes. Additional discussion on the application of pattern recognition techniques to petroleum exploration data is found in deFigueiredo (1982).

Little attention has been given to symbolic waveform representations for seismic interpretation. The notable exception has been Huang and Fu (1986) who applied Syntactic Pattern Recognition, with Error Correcting Parsing, and Hough transforms to classifying bright spots in reflection seismic data. Both individual waveforms and two dimensional reflector shapes were considered. The waveform representation consisted of strings of primitives which described the slope between succesive samples along the wavelet.

Lu and Cheng (1985) used modifications of relational trees along with a sophisticated tree matching procedure to perform correlations between

well-log waveforms. We shall adopt a similar approach for our work.

Since human seismic interpreters frequently comtemplate waveform characteristics which are not strictly based on a physical model for seismic reflection, we may assume that the techniques of visual seismic waveform classification are not necessarily limited to use on seismic signals. This allows us to look outside the field to other areas of waveform interpretation. Several researchers have investigated automated syntactic/semantic electrocardiogram (ECG) analysis algorithms. Perhaps by examining the work done here, we can gain some insight into the seismic interpretation problem.

Horowitz (1975), developed a grammar based technique for detecting and labeling significant waveform peaks. The waveforms are first segmented via a split and merge algorithm. The segments are then given labels, allowing the entire waveform to be parsed according to a predefined grammar. The parser expects strings which are sequences of peaks and linear segments.

Papakonstantinou, et. al. (1981), worked with waveforms described by attributed grammars. These are grammars which are augmented by numerical semantic information. Including such information allows a parser not only to describe a waveform's structure, but to infer meaning from that structure as well. These researchers speculate that such a system would be useful for ECG interpretation.

An elaborate and application-oriented system for ECG waveform interpretation has been developed by Birman (1982). The system, known as SEEK, has been developed as an aid to ECG interpreters. The system encodes ECG waveforms syntactically, also including semantic information for a richer signal description. A rule-based expert system then searches for significant patterns within the waveform and labels them for use by the interpreter. Such a system is not meant to replace, but to assist them.

Recently, Bunke et. al. (1984) investigated syntactic methods for interpreting heart-volume curves. Input curves are represented by regular expressions, then the network of all possible curves is searched untill the most likely match is found. This is similar to error correcting parsing. The system associates certainty factors with strings when deciding on a match.

Most of the techniques described above rely on string grammars. While

strings do a good job of representing the sequence of patterns, they do not sufficiently describe the overall global structural characteristics that we are interested in. To capture this structural information, researchers have turned to higher-dimensional syntactic representations. The simplest of these representations, and the data structure we shall investigate here, is the tree. Trees allow a hierarchical description of signals. Frequently, complex waveforms may be divided into a few major substructures. These in turn may be divided and subdivided until some terminal feature is encountered. We shall now describe a tree representation which segments waveforms according to nested peaks and valleys. This tree structure is known as the relational tree.

THE RELATIONAL TREE REPRESENTATION

The relational tree (RT) provides a two-dimensional description of a one-dimensional signal (Erich and Foith, 1976). It draws on the intuitive notion of a waveform as a sequence of peaks and valleys. The RT structure contains only information about the relative size and placement of peaks and valleys in the signal. Attributes may be added to the nodes of the tree to supply semantic information such as absolute time and magnitude. This structure is insensitive to monotonic scaling of the domain axis.

Each non-terminal node in an RT represents a valley in the waveform. Each terminal node represents a peak. The valleys are nested according to relative depth. The root node of the RT is chosen to represent the deepest valley in the waveform. This divides the waveform into two segments; one to the right of this valley, and one to the left. The descendants of this node will be RT's describing each segment. Each root node is labeled by its dominant peak, i.e. the highest peak in either segment. The non-terminal descendants of any node represent the deepest valleys in the right and left segments. They are in turn labeled by their dominant peaks (see figure 1 a & b). If a segment contains only a peak and no valleys, it is represented by a terminal node and then labeled by that peak.

An important property of RT's is that they partition the set of one-dimensional functions into equivalence classes. The partitions may be

viewed as clusters in a pattern space. The nature of the relational tree structure allows us to classify functions based on that structure.

The node labeling scheme adopted by Erich and Foith was sequential as shown in figure 1. This labeling scheme leads to a sort of context sensitivity, i.e. choosing a label for a peak depends on the labels which have already been assigned to surrounding peaks. To avoid this problem, the convention introduced in our research is to label peaks by their relative size within the waveform segment (see figure 2). Peak heights are scaled and quantized to L levels. When labeled in this manner, all relational trees will have root label P_{L-1}. The smallest peak in a segment will have label P_0. Although this labeling scheme avoids the problem of context sensitivity, it also leads to non-unique labels for peaks. A further modification is to give the root node a unique label, P_L. This allows for more powerfull tree processing.

Researchers have defined alternate tree structures for describing waveforms (Lu and Cheng, 198_). These more complex tree structures borrow from the relational tree concept. The results are trees whose topology represents vertical and horizontal quantization in addition to the relative placement of peaks and valleys. For this work, however, we desire the simplicity of the relational tree sturcture. It should be kept in mind that any of these more complex structures could be substituted. The choice of tree structure should depend on the amount of quantization information required for the specific application.

TREE DISTANCES AND TREE SPACES

Many techniques have been proposed to measure the distance between two trees. We shall employ a tree-to-tree distance algorithm descibed by Lu (1979). The distance $d(\alpha,\beta)$, where α and β are trees, is defined as the minimum number of node insertions, deletions or substitutions necessary to derive one tree from the other. When this distance exists, it obeys the following restrictions on a metric:

1) $d(\alpha,\alpha) = 0$,

2) $d(\alpha,\beta) = d(\beta,\alpha)$,

3) $d(\alpha,\beta) \leq d(\alpha,\gamma) + d(\gamma,\beta)$

Given this metric, we can begin to think of tree spaces, and what they represent. Also, we can answer the question; what operations are possible in a tree space?

A tree space is a directed graph. Each node in the graph represents a tree, and edges exiting each node represent elemetary operations on that tree. Figure 3 shows a subset of trees and the corresponding tree subspace. Only insertion and deletion edges are included. In the figure, path b is shortest, and therefore, the distance between trees one and six is two edge traversals.

Just as patterns may be clustered in a feature vector space, trees can be clustered in a tree space. We shall attack the problem of seismic wavelet interpretation by converting waveforms to trees and partitioning them into clusters in a relational tree space.

PROBLEM STATEMENT AND SOLUTION

The problem we wish to address is that of stratigraphically analyzing a seismic reflection which may be distorted by varying lithology, and corrupted by noise. Suppose an interpreter knows that the presence of a sand lens causes an anomalous reflection at a given horizon. He has some idea of the structural character of the anomaly, but the exact waveform is highly variable. The traditional approach to this problem is visual inspection by an experienced interpreter.

We now describe an automated solution to this problem which makes use of relational tree structures and traditional pattern recognition. The system requires some training set of waveforms. This training set might come from data collected over a producing field, or from synthetic seismograms. The reflection of interest is extracted from each training trace and converted to its relational tree representation. Each tree is assigned to a cluster depending on its character. These training clusters are then used to design a tree transformation [Gecseg and Steinby, 1984] which maps the set of relational trees to a subset of relational trees. This mapping is done so that the resulting clusters are compact and well-separated according to the tree metric defined above. The tree transformaiton has the additional benefit of reducing the number of nodes in

each tree, thereby reducing the complexity of the entire system. The tree transformation is comparable to linear discriminants as they are used in feature space clustering. The reflection of interest is then extracted from traces where the geology is unknown. The extracted wavelets are assigned to the existing clusters via a k-nearest-neighbor algorithm. If an unknown reflection's relational tree falls near an anomalous cluster in tree space, the waveform is said to exhibit the same anomaly as the others in that cluster. The block diagram shown in figure 4 depicts such a waveform classification scheme.

THE TREE TRANSFORMATION

In traditional feature space clustering, the classification error is often minimized by finding an appropriate linear transformation on the feature space. This can be reduced to a simple unconstrained minimization problem. Since we lack such tools as matrix multiplication when dealing with trees, finding the proper transformation to improve cluster separation becomes a search problem. A tree transformation is based on a tree tranducer. The formal definition of a tree transformation is given by Gecseg [11], and lays the foundation for ameliorating clusters in a tree space.

Such a transformation operates on an input tree by starting at the leaves and working upwards to the root. A node may be transformed when all of its children have been transformed. The transform actually inserts states in the tree to act as place markers untill a node is ready for transformation. The variables of the transformation are known as rewriting rules. These rules represent mappings from subtrees in the input forest (augmented with states), to subtrees in the output forest. A transformation is tailored to a specific application by choosing the proper rewriting rules.

A Tree Clustering Objective Function

Once the data undergoes a transformation, the effect on overall cluster compactness and separateness must be assesed. We introduce an objective

function here which is the ratio of between-class to within-class scatter.

For the two class problem, we define the within-class scatter for a transformed cluster of size $|Yi|$ as:

$$s_i = \frac{1}{|Yi|^2} \sum_{y \in Yi} \sum_{x \in Yi} d(y,x)$$

and the between-class scatter S_B as:

$$S_B = \frac{1}{(|X1||X2|)} \sum_{x1 \in X1} \sum_{x2 \in X2} d(x1,x2)$$

Xi and Yi are transformed clusters of trees. $|X_i|$ is the number of sample trees in Xi and d(x,y) is some metric between trees. The objective function for the two class case is:

$$J(X) = \frac{S_B}{(s1 + s2)}$$

This may be easily generalized to c clusters, where c is greater than two.

TREE TRANSFORM DESIGN

The transform design procedure is implemented as an AI production system. Candidate transform rules are chosen by a human expert, and an optimal path search algorithm chooses those rules which maximize the objective function. Ths search is performed such that preference is given to those tree transforms with the fewest rules. this search is time consuming, but by setting an objective function threshold, the entire set of rule combinations need not necessarily be considered.

SIMULATIONS

We shall now apply te waveform recognition system to simulated seismic data and observe the results. Figure 5, quoted from AAPG memoir no. 26, shows a typical seismogram of a thin sand imbedded in a shale. An expert

seismic interpreter can easily spot such an anomaly. A wavelet with a single peak and a trough becomes a doublet over the sand lens. It is not so easy for a machine to make such a qualitative judgement. Due to varying frequencies, noise contamination, changing bed thickness, and segmentation errors, a purely numerical algorithm technique, such as a matched filter, may not succeed in identifying those traces that contain sand. However, this is an ideal two-class relational tree clustering problem.

A seismogram over a known sand lens will serve as a training set of waveforms. From the corresponding relational trees, a tree transform can be found which improves clustering performance based on the objective function described earlier. Seismic traces from unknown geology may then be compared to the two clusters and classified as belonging to the cluster of their nearest k neighbors. Figure 6 depicts schematically the two waveforms in question and their relational trees. Variations of these trees will occur due to noise, changing geology, etc.. The tree transformation will be designed to eliminate these inhomogeneities as much as possible. The rates of successfull classification will be compared before and after transforming the tree clustering space by simulating the waveforms, distorting them, and adding noise, then applying the classification procedure.

The number of peak quantization levels used in this example was six. This provided reasonable identification of critical peaks, while keeping the tree grammar small enough to work with.

Seismic Classification Results

Waveforms were simulated allowing for variations in horizontal intervals. Colored gaussian noise was then added. Also, waveforms were taken from figure 5 and tested. Figure 7 gives the results of transformation and classification for various signal to noise ratios.

DISCUSSION OF RESULTS

The results of this experiment can be compared to the existing numerical techniques. Since within each signal class there are infinitely many variations in the waveform, an infinite number of matched filters

would be required to accurately represent the problem. Assuming the signal set could be limited to a finite number of possible forms, a bank of matched filters would perform better than the technique presented here at low SNR's, but not as well for high SNR's. When the amplitude of the noise becomes large enough to distort the peak dominance relations in the tree representation, the method breaks down. A further consideration is the complexity of the system. Banks of matched filters are difficult to implement, and require many fixed or floating point operations. The relational tree clustering technique, once the transform operations have been selected, requires only addressing operations and integer comparisons.

The power of the tree transformation might be enhanced by taking semantic information into account. If the single attribute "valley height" was to be included at each non-terminal node in the relational tree, more intelligent filtering could take place. It was the inability to distinguish absolute valley depths that limited the success of the system at low signal to noise ratios. The inclusion of at least some semantic information is evidently crucial for the recognition of complex waveforms. The theory for handling semantic information in the tree transform needs to be thoroughly developed before any improvements can be made to the implementation.

CONCLUSION

We have endeavored to construct a system which will identify and classify waveforms based on their underlying structural similarities. The relational tree is a computer data structure that represents a waveform by the relative placement of peaks and valleys. We can treat the relational tree much as a vector in pattern space. Using a tree metric and many of the concepts from traditional cluster analysis, we have designed a waveform recognition system which employs a tree transformation.

After implementing the waveform recognition system and testing it on simulated reflection seismic data, the following observations can be made.

(1) The symbolic recognition system in its present form is only feasible if the tree complexity is low, i.e. the signal contains a small number of peaks and valleys.

(2) For these waveforms, the classification error is equal to or better than numerical techniques at low signal to noise ratios, but abruptly becomes worse as relative peak and valley heights are altered by noise.

(3) The transform effectiveness could be greatly enhanced by adding semantic information, but the theory governing such a transform has yet to be developed.

REFERENCES

Birman, Kenneth P., 1982, Rule-based learning for more accurate ECG analysis; IEEE Trans. PAMI, Vol 4, No. 4, 369-380.

Bunke, H., Grebner, K., Sagerer, G., 1984, Syntactic analysis of noisy input strings with an application to the analysis of heart-volume curves; Proc. 1982 IEEE Conf. PRIP, 1145-1147.

Chapman, F. E. and Schafers, C. J., 1983, Shallow sand channel, coal exploration, Illinois Basin, *in* Seismic expression of structural styles; AAPG Studies in Geology, Vol. 1, 33-34.

deFigueiredo, Rui J. P., 1982, Pattern recognition approach to exploration, *in* K. C. Jain, and R. J. P. deFigueiredo, Concepts and techniques in oil and gas exploration; SEG.

Dobrin, Milton B., 1977, Seismic exploration for stratigraphic traps, *in* Seismic stratigraphy - applications to hydrocarbon exploration; AAPG memoir 26.

Ensley, R. A., 1985, Evaluation of direct hydrocarbon indicators through comparison of compressinal- and shear-wave seismic data: A case study of the Myrnam Gas Field, Alberta; Geophysics, Vol. 50, No. 1.

Erich, R. W., and Foith, J. P., 1976, Representation of random waveforms by relational trees; IEEE. Trans. Computers. Vol. c-25., 725-736.

Focht, G. W. and Baker, F. E., 1985, Geophysical case history of the Two Hills Colony Gas Field of Alberta; Geophysics, Vol. 50, No. 7.

Gecseg, F., and Steinby, M., 1984, Tree Automata; Akademiai Kiado., Budapest.

Horowitz, Steven L., 1975, A syntactic algorithm for peak detection in

waveforms with applications to cardiography; Comm. of ACM, Vol. 18, No. 5, 281-285.

Huang, K. Y., and Fu, K. S., 1986, Syntactic pattern recognition for the recognition of bright spots; Pattern Recognition, Vol. 18, No. 6, 421-428

Lu, S. Y., 1979, A tree-to-tree distance and its application to cluster analysis; IEEE. Trans. PAMI Vol PAMI-1., No. 2., 219-224.

Lu, S. Y., and Cheng, 1985, Waveform correlation by tree matching; IEEE. Trans. PAMI, Vol. 7, No. 3, 299-305

Mathieu, P. G. and Rice, G. W., 1969, Multivariate analysis used in the detection of stratigraphic anomalies from seismic data; Geophysics, Vol. 34, No. 4, 507-515.

Neidell, Norman S., and Poggiagliolmi, Ello,, 1977, Stratigraphic modeling and interpretation - geophysical principles and techniques, *in* Seismic stratigraphy - applications to hydrocarbon exploration; AAPG Memoir No. 26, 389-416.

Papakonstantinou, George K., 1981, An interpreter of attribute grammars and its application to waveform analysis; IEEE Trans. Softwave Engineering, Vol. 7, No. 3.

Shaw, S. W., and deFigueiredo, R. J. P., 1986, Processing waveforms as trees for pattern recognition; Rice University Tech. Report, No. 8604, (To be submitted for publication).

Sherrif, Robert E., 1977, Limitations on resolution of seismic reflection and geologic detail derivable from them, *in* Seismic stratigraphy - applications to hydrocarbon exploration; AAPG memoir 26.

Sinvahl, A. K., Khattri, N. Sinvahl, H. and Awasthi, A. K., 1984, Seismic

indicators of stratigraphy; Geophysics, Vol. 49, No. 8, 1196-1212.

Waters, K. H. and Rice, G. W., 1975, Some statistical and probabilistic techniques to optimize the search for statigraphic traps using seismic data; 9th World Petroleum Congress, Tokyo.

LIST OF FIGURES

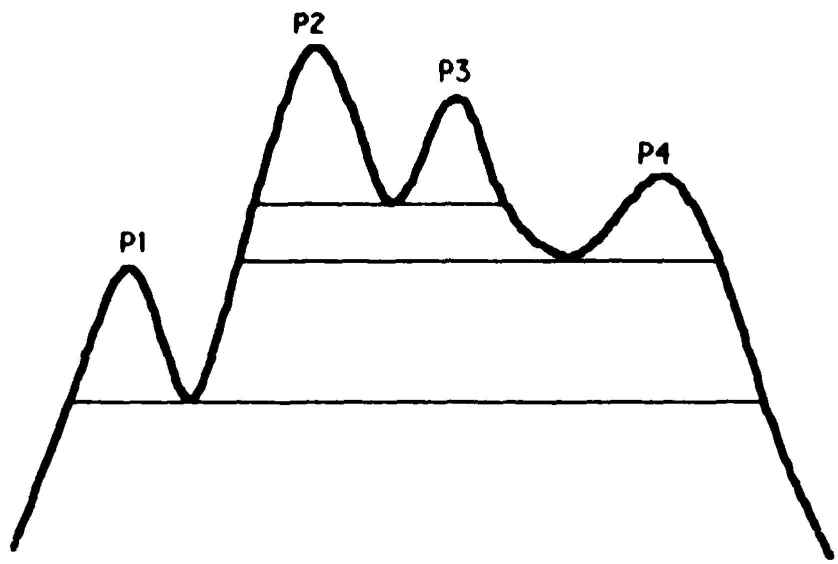


Figure 1a
Waveform Segments

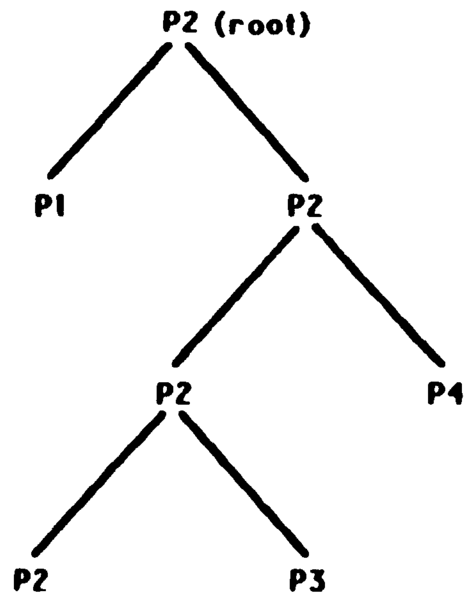


Figure 1b
The Relational Tree

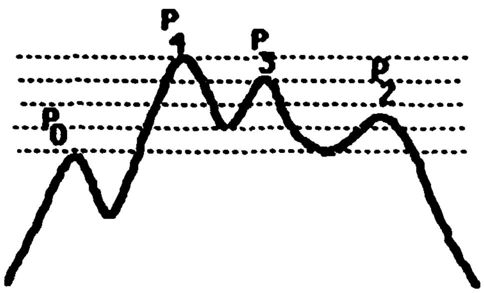


Figure 2
Modified Peak Labeling Scheme

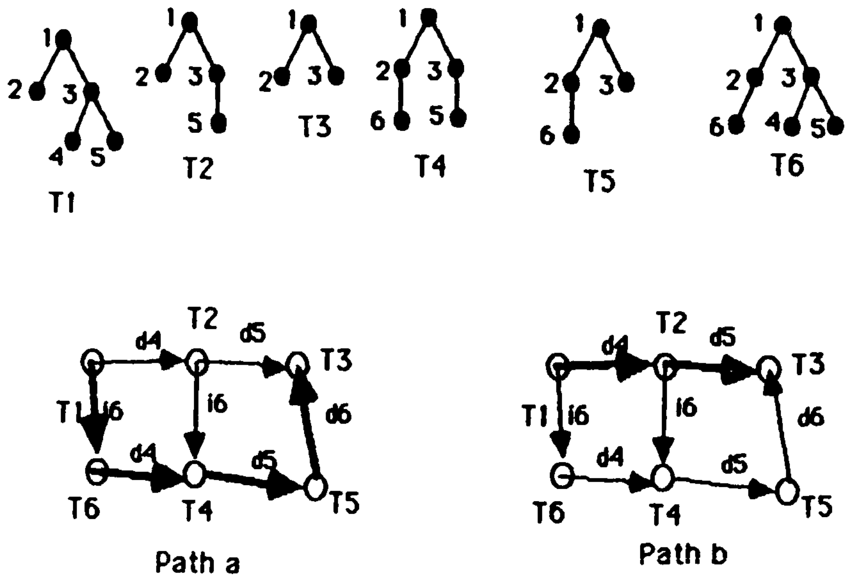


Figure 3
A Tree Subspace. Path b is the minimum distance.

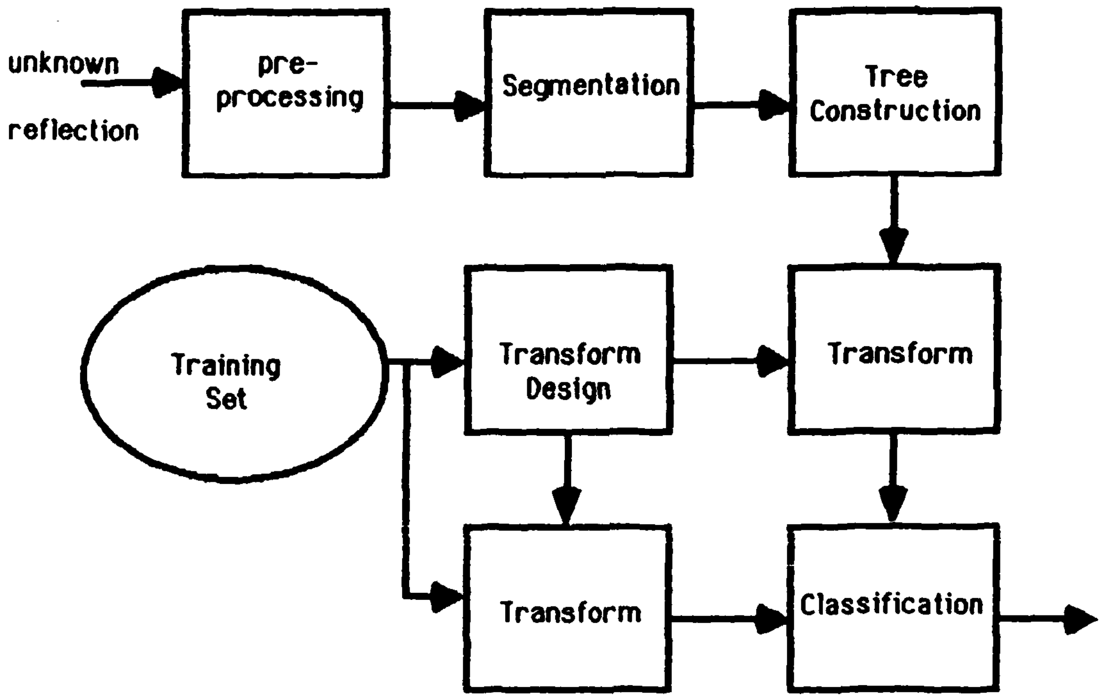


Figure 4
The Relational Tree Waveform Classification System

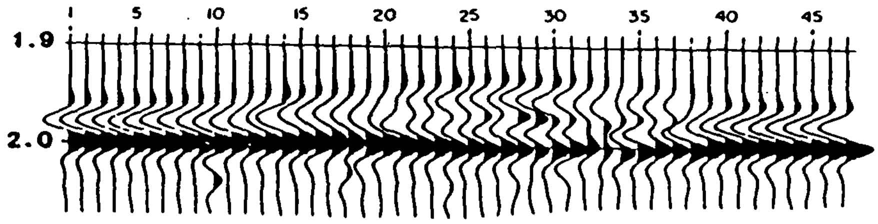


Figure 5
Seismogram over a sand imbedded in shale (after Neidell (1977))

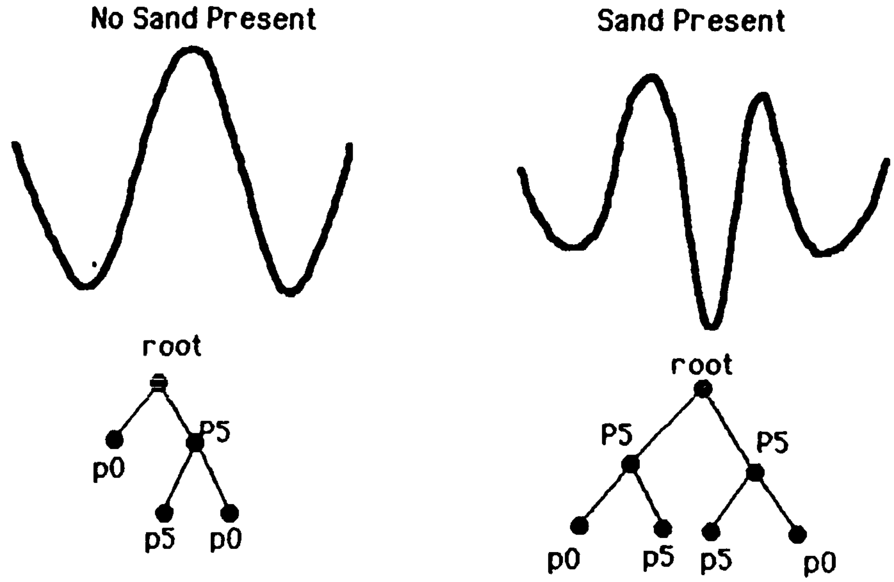


Figure 6
Seismic Waveforms and Relational Trees

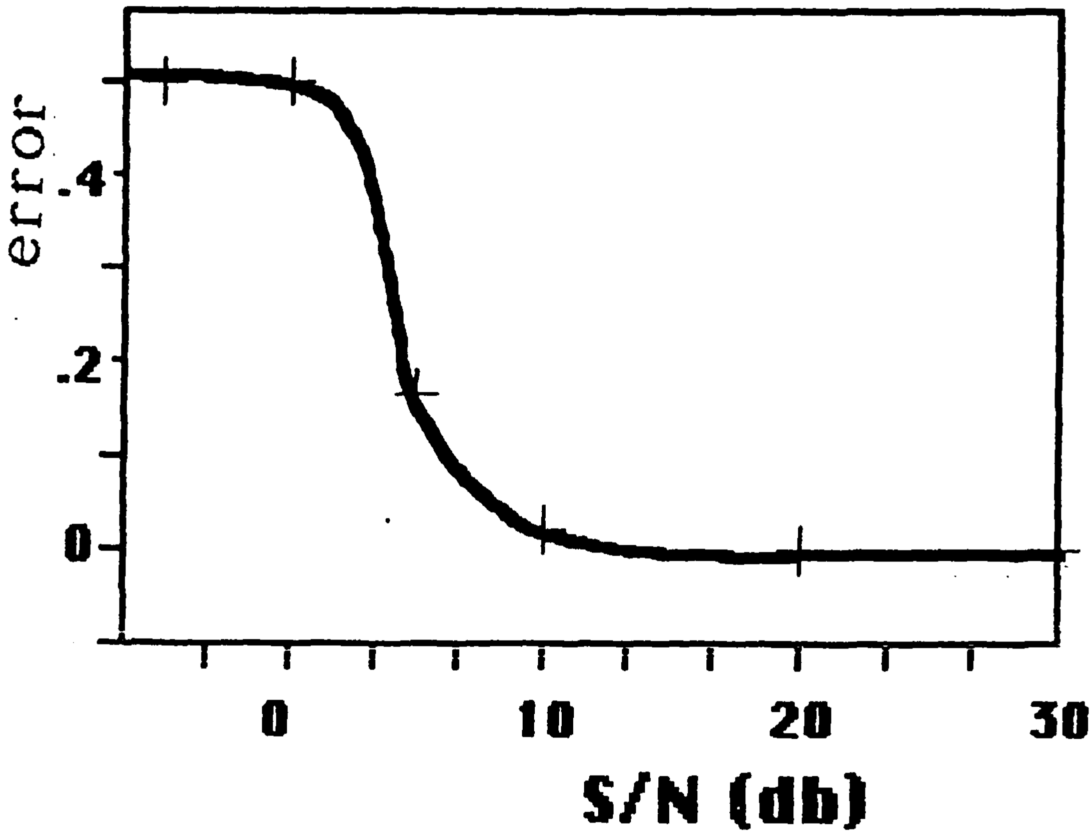
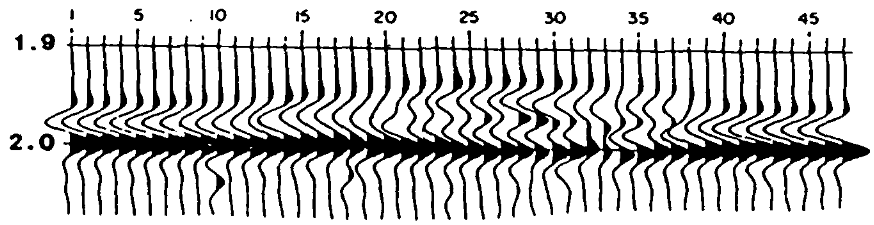


Figure 7

Results of classifying seismic wavelets with the relational tree system



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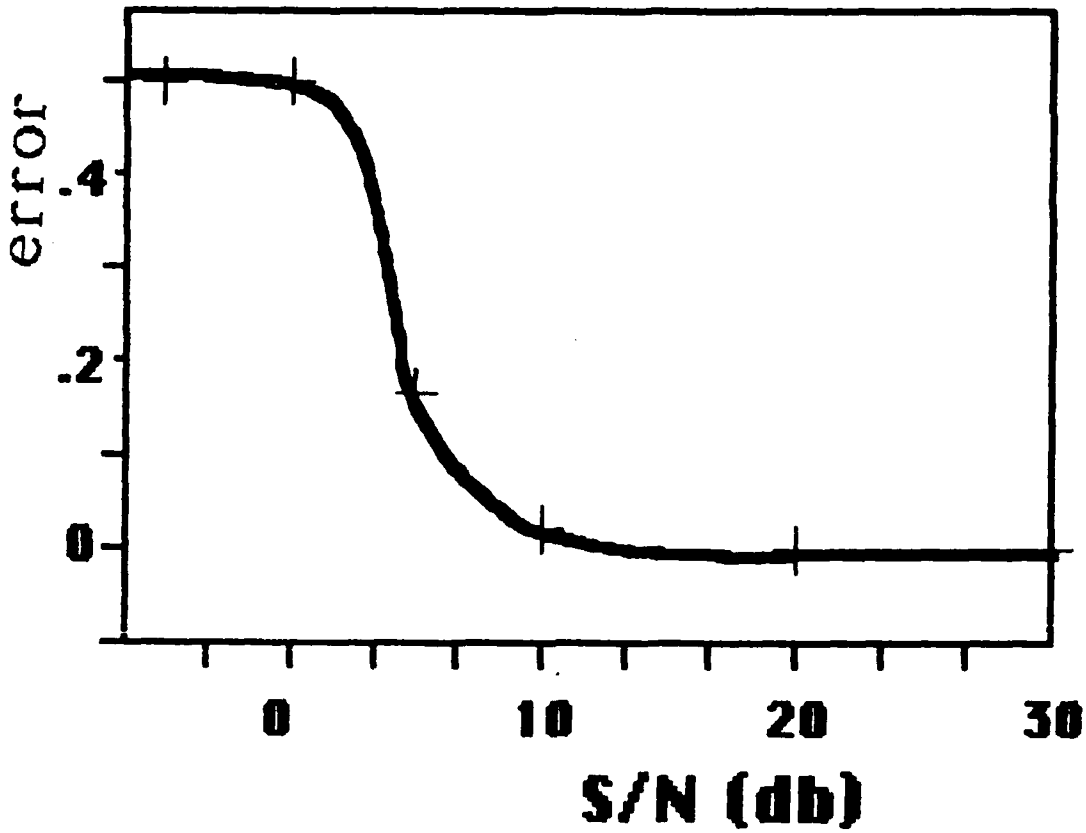

Figure 7

Results of classifying seismic wavelets with the relational tree system

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